NSWCCD-61-TR–2005/05 MODELING OF HIGH CARBON AND HIGH NICKEL STEEL: EFFECT OF HEAT TREATEMENT TIME

Naval Surface Warfare Center
Carderock Division
West Bethesda, MD 20817-5700

NSWCCD-61-TR–2005/05 January 2005

Survivability, Structures, and Materials Department

Technical Report

MODELING HIGH CARBON AND HIGH NICKEL STEEL: EFFECT OF HEAT TREATMENT TIME

by

A. Srinivasa Rao

Naval Surface Warfare Center
Carderock Division
West Bethesda, MD 20817-5700

NSWCCD-61-TR–2005/05 January 2005

Survivability, Structures, and Materials Department

Technical Report

MODELING HIGH CARBON AND HIGH NICKEL STEEL: EFFECT OF HEAT TREATMENT TIME

by

A. Srinivasa Rao

This page intentionally left blank

REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. REPORT DATE *(DD-MM-YYYY)* Jan 2005	**2. REPORT TYPE** Research and Development	**3. DATES COVERED** *(From - To)* -
4. TITLE AND SUBTITLE Modeling High Carbon and High Nickel Steel: Effect of Heat Treatment Time (HTt)		**5a. CONTRACT NUMBER**
		5b. GRANT NUMBER
		5c. PROGRAM ELEMENT NUMBER 0603563N
6. AUTHOR(S) A. Srinivasa Rao		**5d. PROJECT NUMBER**
		5e. TASK NUMBER
		5f. WORK UNIT NUMBER
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) AND ADDRESS(ES) NAVAL SURFACE WARFARE CENTER CARDEROCK DIVISION 9500 MACARTHUR BOULEVARD WEST BETHESDA, MD 20817-5700		**8. PERFORMING ORGANIZATION REPORT NUMBER** NSWCCD 61-TR-2005/05
9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES) NAVAL SEA SYSTEMS COMMAND ATTN SEA 05M2 (METALLIC MATERIALS ADV DEV & CERT PROG) WASHINGTON NAVY YARD DC 20376		**10. SPONSOR/MONITOR'S ACRONYM(S)**
		11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION / AVAILABILITY STATEMENT
Distribution unlimited. Approved for public release.

13. SUPPLEMENTARY NOTES

14. ABSTRACT

In order to understand the effect of heat treatment on the mechanical properties such as the yield strength (s (02%)), ultimate stress (Su), deformation (d (%)), reduction in area of cross section (RA(%)) and Charpy v-notch test (CVN) values, a neural network analysis approach was undertaken to analyze the data obtained on 10% nickel steel. Initially the neural network was trained using the experimental data collected from 121 data sets from 10 different steel samples that were heat treated at temperatures in the range 950 – 1,050 °F, and for up to 1200 minutes. There was insufficient data to run the neural network analysis using the neural mode of analysis. The network analysis was made using the genetic mode over a very small heat treatment range (up to 600 min). The predicted values were then added as additional input to retrain the neural network. By repeating the above procedure three times, final neural network analysis was carried out to predict the properties of steel as a function of heat treatment time (1200 min.). There was not enough data on the CVN values to perform any mode of neural network analysis. The final predictions on the mechanical properties results conclude that the heat treatment at a given temperature (in the range 950 – 1050 °F) for up to 300 minutes has some effect on the s (02%), Su, d (%), and RA(%) values. However, prolonged heat treatment above 300 minutes and up to 1200 minutes has no significant effect.

15. SUBJECT TERMS
Modeling, High Carbon and High Nickel Steel, Heat Treatment Time, Neural Network Analysis

16. SECURITY CLASSIFICATION OF:			**17. LIMITATION OF ABSTRACT**	**18. NUMBER OF PAGES**	**19a. NAME OF RESPONSIBLE PERSON** A. SRINIVASA RAO
a. REPORT UNCLASSIFIED	**b. ABSTRACT** UNCLASSIFIED	**c. THIS PAGE** UNCLASSIFIED	**SAA**	**36**	**19b. TELEPHONE NUMBER** *(include area code)* 301-227-5141

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std. Z39.18

This page intentionally left blank

Contents

Figures

Tables

Administrative Information

The work described in this report was performed at the Naval Surface Warfare Center, Carderock Division (NSWCCD), West Bethesda, MD in the Survivability, Structures and Materials Department (Code 60) by personnel in the Metals Division (Code 61). The work was funded by the Naval Sea Systems Command (SEA 05M2), Washington D.C., the Metallic Materials Advanced Development and Certification Program PE # 0603563N, managed by Mr. Gene Mitchell.

Executive Summary

In order to understand the effect of heat treatment on the mechanical properties such as the yield strength (s (02%)), ultimate stress (Su), deformation (d (%)), reduction in area of cross section (RA (%)) and Charpy v-notch test (CVN) values, a neural network analysis approach was undertaken to analyze the data obtained on 10% nickel steel. Initially the neural network was trained using the experimental data collected from 121 data sets from 10 different steel samples that were heat treated at temperatures in the range 950 – 1,050 °F, and for up to 1200 minutes. There was insufficient data to run the neural network analysis using the neural mode of analysis. The network analysis was made using the genetic mode over a very small heat treatment range (up to 600 min). The predicted values were then added as additional input to retrain the neural network. By repeating the above procedure three times, final neural network analysis was carried out to predict the properties of steel as a function of heat treatment time (1200 min.). There was not enough data on the CVN values to perform any mode of neural network analysis. The final predictions on the mechanical properties results conclude that the heat treatment at a given temperature (in the range 950 – 1050 °F) for up to 300 minutes has some effect on the s (02%), Su, d (%), and RA (%) values. However, prolonged heat treatment above 300 minutes and up to 1200 minutes has no significant effect.

Introduction

The metallurgical study of 10 % nickel steel plates has concluded that these steels have superior strength and toughness. Being a potential candidate steel for US Navy applications, detailed metallurgical testing and evaluations have been carried out on these steels and the final findings on the microstructure - property relationships were well documented [1]. The report contains a detailed analysis of the effect of tempering temperature, time, and mechanical properties including strength, ductility, impact energy and fracture toughness etc.

If one could predict the composition of steel based on its mechanical property requirement, that modeling tool would provide a logistical advantage for material selection processes. With that theme in mind, this project was undertaken to investigate the composition of high nickel steel using neural network based analysis.

The overall goal of this project is to develop new steel compositions with carbon and nickel in the range 0.01 – 0.15 wt.% and 9 – 11 wt.% respectively and, subsequently, predict their mechanical properties, such as strength, ductility, and impact energy. In order to achieve this goal, the objectives are:

1. To construct a learning tree for the high carbon and high nickel steel using the present steel composition and mechanical property data for the neural network analysis. Neural network inputs will include chemical composition, yield strength (s (0.2%)), ultimate strength (Su), ductility (d (%)), reduction in area (RA (%)) impact energy values (CVN at room temperature, CVN at – 94 °F and CVN at –320 °F) and the duration of the heat treatment.

2. To predict the mechanical properties of new steels containing various amounts of carbon (in the range 0.01 – 0.15 wt.%), and/or nickel (in the range 9 – 11 wt.%) respectively.

3. To predict the effect of prolonged heat treatment on the mechanical properties of steels used in the present analysis.

Neural Network Model

In neural networks [2-3], a set of basic functions $V_k(t)$ are used, which may be of three types

(a) Bounded $|V_k(t)| \leq B$ (or may not)

(b) Orthogonal $< V_k(t) \cdot V_m(t) > = K \cdot \delta\,(k-m)$

(c) Continuous

The general form of approximation for the above analytical function can be given as

$$y(x) = \sum_{k=1}^{L} a_k \cdot \nu_k(x) \qquad \text{Eq (1)}$$

where L is the number of basis functions

$\nu_k(x)$ is the k th basis function

a_k is the k th coefficient

x is the input signal.

The solution for a_k can be found using an integral formula [Fourier series], a derivative formula [Taylor Series], or a curve fit to (x_k,y_k) for $1 \leq k \leq N_v$

We can also extend the determination of the network for a multi-variable function. The analytical approximation for the network is given as follows. For conventional multi-variant systems, the approximation of M functions of N variables, the general form of approximation is given as:

$$y_m(x) = \sum_{k=1}^{L} a_{mk} \cdot v_k(x) \qquad \text{Eq (2)}$$

$$y(x) = \sum_{i=1}^{L_1} \sum_{j=1}^{L_2} \cdots \sum_{k=1}^{L_N} a_{m,l,j\,\ldots,k} \cdot v_i(x_1)\, v_j(x_2) \cdots v_k(x_n) \qquad \text{Eq (3)}$$

where $1 \leq m \leq M$;

$V_i(x_k)$ is the i-th basis function of x_k,

$V_k(x)$ is the k th basis function of x, which is a product of N of the $V_i(x_k)$ basis functions.

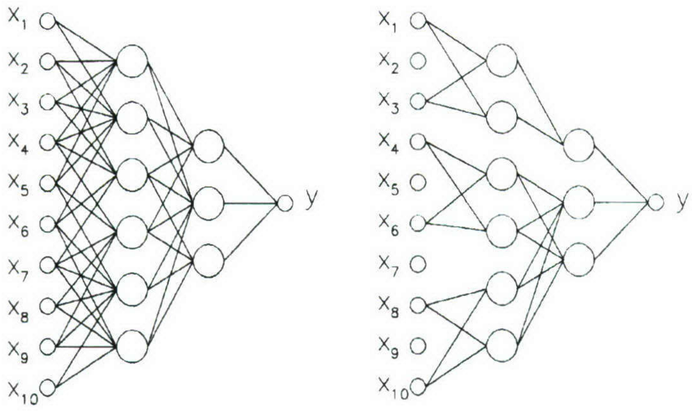
L is the number of multivariate basis functions,

L_k is the number of uni-variant basis functions of x_k used, a_k is the k^{th} coefficient,

x is the input vector of dimension N, and

$Y_m(x)$ is the m^{th} function of N variables.

The exact mapping of the above function is very difficult because L increases with N and this leads to a combinatorial explosion. Therefore by training an algorithm, it is possible to minimize the error function and also control the network. For example, the Figure 2 (a) depicts a network based on every function (X_1, X_2, ---- X_{10}) and Figure 2 (b) depicts a final network that was generated by training the algorithm to follow a path with minimum error function. Thus it is possible to control the basic functions and train the network to find a best fit.



Original Network **Final Network**

(a) **(b)**

Figure 1. Schematic diagram of the working of a network.

Neural Network Analysis

AI Triology, a collection of artificial intelligence and neural network software programs produced by Ward Systems Inc., was used to build the neural network model in this study.

The most important task in developing a neural network is to determine which inputs generate the most accurate predictions. It is also important to determine the magnitude of the training data required to predict the outputs within acceptable limits of error.

In this project, it was decided to develop a neural network tree based on the experimental data from Zhang and Czyryca [1]. A starting database of steel samples with 10 different elemental compositions and 121 different processing conditions were collected. Table 1 shows the chemical composition of all 10 steel samples used for the present study. The processing conditions, the history of the heat treatment; and the experimentally-determined mechanical properties of these steel samples are given in Table 2.

Table 1. The elemental composition (wt.%) of steel.

ISG Heat ID	C	Ni	Mo	Ti	V	S	P	Nb	N	Others	Fe
704H 007	0.092	9.85	1.23	0.026	0.077	0.0007	0.002	0.003	0.003	1.8823	86.8338
704 H 008	0.098	9.85	1.61	0.027	0.149	0.0006	0.002	0.003	0.004	1.8823	86.3745
704 H 009	0.015	9.87	1.23	0.027	0.073	0.0006	0.002	0.003	0.004	1.8823	86.8935
704 H 010	0.15	9.87	1.6	0.027	0.139	0.0006	0.001	0.003	0.004	1.8823	86.3232
704 A 003	0.092	10.3	1.13	0.012	0.067	0.0017	0.007	0.003	0.007	1.8823	86.4982
704 A 002	0.096	10.3	1.12	0.012	0.067	0.0004	0.004	0.003	0.003	1.8823	86.5126
704 A 006	0.089	10.3	1.11	0.011	0.071	0.0019	0.007	0.041	0.006	1.8823	86.4806
H 007 78-1	0.11	10.06	1.08	0.015	0.068	0.001	0.004	0	0.006	1.6934	86.9626
SID HT - H31-1	0.092	9.94	1.18	0.004	0.12	0.002	0.006	0.02	0.002	1.2955	87.3382
704 A 007	0.098	10.3	1.12	0.12	0.068	0.0004	0.003	0.003	0.003	1.8823	86.4022

Table 2. Processing conditions, heat treatment temperature (HTT), duration of heat treatment (HTt), the yield stress (s (0.2%)), the ultimate tensile stress (Su), the total elongation (d (%)), the reduction in area (RA(%)), and the Charpy v-notch test (CVN) value measured at – 320 °F (CVN – 320 °F), at – 94 °F (CVN – 94 °F) and at room temperature (CVN RT) respectively for some steel samples used for the network training.

ID			HTT (°F)	HTt (min)	S (0.2%)	Su	D (%)	RA (%)	CVN - 320 °F	CVN - 94 °F	CVN RT
704 H 007	HR	ISG-QT			179	188	19.9	68.2	42.9	97.3	
704 H 007	HR	1450F 1h AC	1450	60	147	203	15.2	64.5		71	110
704 H 007	HR	1450F 1h WQ	1450	61	165	204	14.4	61.1		67	
704 H 007	HR	H.R.	27	60	138	197	15.3	61.7		103	
704 H 007	HR	400F10m	400	10	167	195	15.5	67.3		83.5	119
704 H 007	HR	950F10m	950	10	173	183	15.9	63.9			
704 H 007	HR	950F10m	950	10	176	185	16.3	63.9	18.8	75.6	
704 H 007	HR	950F1h	950	60	173	183	16.6	67.3	16.6	70.6	
704 H 007	HR	950F5h	950	300	177	185	15.6	70.4	13	52.4	
704 H 007	HR	1000F10m	1000	600	177	185	16.3	62.2	17.8	79.7	
704 H 007	HR	1000F1h	1000	60	173	182	16	70.4	17.6	76.6	94
704 H 007	HR	1000F5h	1000	300	175	180	15.6	70.8	15.8	67.6	
704 H 007	HR	1050F10m	1050	10	176	184	16	68.1	19.3	80.8	
704 H 007	HR	1050F1h	1050	60	173	178	15.6	67.3	20.6	82.2	
704 H 007	HR	1050F5h	1050	300	166	169	16	67	29.8	87.6	
704 H 007	HR	1500FWQ,1050F1h	1050	60	170	176	18.1	71		109	
704 H 007	HR	1500FWQ,1050F5h	1050	300	162	166	18.1	69.1		95.8	
704 H 007	HR	1550FWQ,1050F1h	1050	60	167	173	18.6	69.7		121	
704 H 007	HR	1550FWQ,1050F5h	1050	300	160	164	18.2	70.4		115	

Notes: HR : Hot rolled; QT : Quenched and tempered
WQ = water quench, AC = Air cool
1000F 60 m = Heat treatment temperature 1000 °F and heat treatment time 60 min.

Table 2. Continued

ID			HTT (°F)	HTt (min)	s (0.2%)	Su	d (%)	RA (%	CVN - 320 °F	CVN - 94 °F	CVN RT
704 H 008	QT	RT	27	60	140	200	17.8	70	94.2		
704 H 008	88-1	ISG-QT	27	60	183	193	20.2	66	59.9	28.4	104
704 H 008	810-5	950F1h	950	60	176	190	18.7	62.9	36.2		
704 H 008	810-6	950F5h	950	300	180	189	17.1	63.1	28.6		
704 H 008	810-7	1000F10m	1000	10	177	191	18.6	67.6	48.4		
704 H 008	810-8	1000F1h	1000	60	178	188	17.9	61.5	34.5		
704 H 008	810-9	1000F5h	1000	300	175	179	17.9	62.2	36.8		49
704 H 008	810-10	1050F10m	1050	10	181	190	18.1	60.4	41.2		
704 H 008	810-11	1050F1h	1050	60	173	179	18.4	58.7	45		
704 H 009	810-12	1050F5h	1050	300	148	155	19.5	62	67.8		71
704 H 009	RT	H009,RT	27	60	189	201	20.1	67.3		52.4	
704 H 009	98-1	ISG-QT*	950	10	188	200	19.8	65	30.3	52.4	68
704 H 009	X1	950F 10m	950	10	184	194	16.6	65.6		42.8	68
704 H 009	X2	950F 10m	950	60	185	195	16.7	61.9			
704 H 009	X3	950F 1h	950	60	187	195	16.1	64.2		42.4	
704 H 009	X4	950F 1h	950	60	186	197	17.8	57.1			
704 H 009	X5	950F 1h	950	60	189	197	17.1	64.7		40	
704 H 009	X6	950F 1h	1000	10	188	196	16.5	63.7			
704 H 009	X7	1000F 10 m	1000	10	184	195	17.3	64.4		45	
704 H 009	X8	1000F 10 m	1000	60	185	195	17.7	61.9			
704 H 009	X9	1000 F, 1h	1000	60	187	196	16.4	62.4		44.4	
704 H 009	X10	1000 F, 1h	1000	300	187	197	16.6	62.5			
704 H 009	X11	1000F, 5h	1000	300	187	195	16.2	62.4		43	
704 H 009	X12	1000F, 5h	1050	10	185	194	15.5	62.2			
704 H 009	X13	1050F, 10 m	1050	10	186	196	16.7	66.3		50.6	
704 H 009	X14	1050F, 10 m	1050	60	185	194	17.2	65.1			
704 H 009	X15	1050F, 1h	1050	60	186	194	16.2	66.3		49.8	
704 H 009	X16	1050F, 1h	1050	300	186	193	16.6	61.9			
704 H 009	X17	1050F, 5h	1050	300	178	182	18.5	66.6		53.6	
704 H 009	X18	1050F, 5h			178	182	16.7	64.2			
704 H 010	08-1	ISG-QT	27	10	195	208	20	63.1	26.3	48.5	
704 H 010	011-1	1450F 1h AC	1450	60	154	228	15	55.6		36	
704 H 010	011-2	1450F 1h WQ	1450	60	176	233	13	52.3		29.8	61
704 H 010	011-3	H.R.			143	221	16.3	67.3		74.8	
704 H 010	011-4	950F10m	950	10	188	203	18.2	59.2		34	
704 H 010	011-5	950F1h	950	60	191	204	15.2	58.2		28.6	92.5
704 H 010	011-6	950F5h	950	300	197	208	16.8	55.6		25	
704 H 010	011-7	1000F10m	1000	10	189	203	16.2	60.2		35.4	
704 H 010	011-8	1000F1h	1000	60	193	203	15.2	58.7		28	
704 H 010	011-9	1000F5h	1000	300	193	198	14.6	57.6		29.3	

Notes: HR : Hot rolled; QT : Quenched and tempered
WQ = water quench, AC = Air cool
1000F 60 m = Heat treatment temperature 1000 °F and heat treatment time 60 min.

Table 2. Continued

ID			HTT (°F)	HTt (min)	s (0.2%)	Su	d (%)	RA (%	CVN - 320 °F	CVN - 94 °F	CVN RT
704 H 010	011-10	1050F10m	1050	10	194	202	16.1	58.2		34.4	
704 H 010	011-11	1050F1h	1050	60	193	199	16.7	59.2		35.5	42
704 H 010	011-12	1050F5h	1050	300	180	185	19	55.6		45.4	
EAFE	L25	1500F1hWQonly	1500	60	164	207	17.7	58.7		35.3	45
EAFE	L26	1500F1hWQ	1500	60	162	208	16.7	60.2			
EAFE	L16	1500WQ1000F1h	1000	60	165	178	23.4	65			
EAFE	L17	1500WQ1000F5h	1000	300	169	177	20.5	68.9		63.3	
EAFE	L18	1500WQ1000F5h	1000	300	171	177	21.2	65			
EAFE	L19	1500WQ1050F10m	1050	10	161	175	21.8	70.9		66.3	
EAFE	L20	1500WQ1050F10m	1050	10	163	176	22.7	68.7			
EAFE	L21	1500WQ1050F1h	1050	60	164	175	21.5	68.5		76.5	
EAFE	L22	1500WQ1050F1h	1050	60	167	177	21.4	70.8			
EAFE	L23	1500WQ1050F5h	1050	300	162	169	22.4	69.6		65	
EAFE	L24	1500WQ1050F5h	1050	300	162	170	21.3	70.4			
EAFE	L1	1500WQ1100F1h	1100	60	161	168	20.3	69.1		80.5	
EAFE	L2	1500WQ1100F1h	1100	60	165	171	21.5	70.9			
EAFE	L3	1500WQ1100F3h	1100	180	151	161	22.8	70		81.3	
EAFE	L4	1500WQ1100F3h	1100	180	154	161	24.7	66.9			
EAFE	L5	1500WQ1100F5h	1100	300	144	157	24.4	70.4		84.8	
EAFE	L6	1500WQ1100F5h	1100	300	145	155	24.1	71.3			
SID HT-	H31-3	950F300	950	300	165.5	171.7	24.6	71.3	72		
SID HT -	H32-1	1000F10	1000	10	165.1	175.5	23.7	65.8	114.7		
SID HT -	H32-2	1000F60	1000	60	167.5	176.3	25.6	71.6	103.5		
SID HT -	H32-3	1000F300	1000	300	165.1	168.4	23.2	76.1	93.5		
SID HT -	H33-1	1050F10	1050	10	166.7	174.1	22.2	73	113.3		
SID HT -	H33-2	1050F60	1050	60	163	169.8	23.5	74.8	126.7		
SID HT -	H33-3	1050F300	1050	300	147.6	151.9	22.6	72.3	119.7		
SID HT -	H34-1	1100F10	1100	10	165.4	170.7	23.5	72.8	115		
SID HT -	H34-2	1100F60	1100	60	152.9	158.8	22.4	77.2	132		
SID HT -	H34-3	1100F300	1100	300	104	131.3	26.2	77.9	138		
SID HT -	H35-1	1200F10	1200	10	127.2	151.4	25.1	79.5	135		
SID HT -	H35-2	1200F60	1200	60	111.2	143.8	22.5	74	131		
SID HT -	H36-3	800F90min	800	90	160.5	176.6	21.4	69.6			
SID HT -	H36-4	1050F110m(-94)	1050	110	174	175	22.2	73			
SID HT -	H38-1	AN+950F10m	950	10	148	170	25.7	70.9	111		
SID HT -	H38-2	AN+950F60m	950	60	147	170	23.6	74.2	108		
SID HT -	H38-3	AN+1000F10m	1000	10	146	166	25.3	71.7	114		
SID HT -	H38-4	AN+1000F60m	1000	60	146	166	26.9	74.6	116		
SID HT -	H39-1	AN+1050F10m	1050	10	142	166	25.7	72.1	118		
SID HT -	H39-2	AN+1050F60m	1050	60	138	162	24.2	73.8	130		

Notes: HR : Hot rolled; QT : Quenched and tempered
WQ = water quench, AC = Air cool
1000F 60 m = Heat treatment temperature 1000 °F and heat treatment time 60 min.

Once the inputs are defined, it is important to decide which algorithm is to be used in order to train the network. The software has the capacity to train the network in a "neural mode" and in a "genetic mode." An advantage of the neural mode is that it trains the network more quickly than the genetic training strategy.

The network training in genetic training mode takes longer to train but this mode can make predictions with fewer data. However, the genetic training mode is limited in its predictability. It cannot predict the properties of the alloys that are out of the range of the training data. When we ran the program using the neural mode, the program stopped because of insufficient data points. Since the input data is enough to run the neural network program under genetic training mode, we used the genetic training mode to predict the properties of steel samples. We was found that the present set of data points were not enough to make reasonable predictions using neural mode. Therefore, the data was first trained using the generic mode. Once, the network was trained, neural network predictions were made for short intervals of heat treatment conditions. These predicted data points were added as input data in order to generate more a neural mode of predictions. The network training sequences are as follows.

In the first training, the inputs for the network were the elemental composition, heat treatment temperature, heat treatment time and all the values of the measured mechanical properties [s (0.2%), Su, d (%), RA (%), CVN values] were fed as input for the network. From the trained network, the yield strength (s (0.2%)) was predicted. The predicted value was used as an additional input to predict the ultimate tensile strength (Su). The predicted Su was then added to the network tree as an input. This cycle was continued until all the predictions were made. It was found that using the predicted values as input one time, improved the correlation. However, it was found that repeating the above procedure did not improve the correlation function.

Results and Discussion

Table 3 shows typical input values and the neural network-based predictions generated using the genetic mode of the neural network analysis. Figures 2 and 3 show the correlation between the actual and predicted values obtained using the genetic mode of the neural network analysis. The results indicate that the present approach of using the genetic mode of the neural network analysis provides a reasonable prediction of the mechanical property of steels. The results shown in Figure 2 suggest that there is a good correlation between the actual and predicted values. The correlation between the experimental and the predicted values are 96.98 % for s (0.2%), 98.01 % for Su; 96.48 % for d (%) and 97.61 % for RA (%), and 99.69 % for CVN (- 94 °F); 99.98 % for CVN (- 320 °F) respectively.

Table 3. Actual and predicted values of yield strength (s (0.2%)), ultimate strength (Su), elongation (d%), reduction in area of cross section (RA (%)) and CVN measured at - 94 °F (CVN – 94 °F) and at – 320 °F (CVN – 320 °F) respectively for heat treatment temperature 1,050 °F.

ISG Heat	**HTt (min)**	**s (0.2%)**	**s (0.2%)**	**Su**	**Su**	**d (%)**	**d (%)**	**RA (%)**	**RA %**	**CVN - 94 °F**	**CVN - 94 °F**	**CVN - 320 °F**	**CVN – 320 °F**
			Pred.		**Pred.**		**Pred.**		**Pred.**		**Pred.**		**Pred.**
H 008 810-10	10	181.2	**186.2**	189.6	**186.8**	18.1	**17.3**	60.3	**58.7**	41.2	**43.2**		**18.9**
H 007J17	10	176.1	**177.6**	183.7	**180.4**	16	**15.6**	68.1	**67.2**	80.8	**78.2**	17.8	**21.5**
H 007J19	60	173.2	**175.2**	178.5	**181.8**	15.6	**15.9**	67.2	**68.0**	82.2	**81.2**	17.6	**21.6**
H 007 J21	300	166.4	**162.4**	168.5	**175**	16	**15.7**	67.0	**67.4**	87.6	**84.7**	19.3	**21.4**
H 007 J23	60	169.9	**167.9**	176.5	**175.5**	18.1	**17.3**	71.0	**70.4**	109.4	**113.8**	20.6	**22.6**
H 007 J24	300	162.4	**160.2**	165.7	**167.2**	18.1	**16.6**	69.0	**67.0**	95.8	**114.5**	29.8	**18.8**
H 007J25	60	166.6	**168.1**	172.8	**172.1**	18.6	**18.2**	69.7	**70.4**	120.8	**103.2**		**22.2**
H 007 J26	300	159.8	**162.4**	163.7	**166.5**	18.2	**18.6**	70.4	**70.4**	115	**104.7**		**22.1**
H 008 810-11	60	173.1	**178.3**	179.1	**178.3**	18.4	**17.8**	58.6	**61.4**	45	**41.1**		**19.0**
H 008 810-12	300	147.9	**159.8**	155.4	**164.2**	19.5	**19.3**	61.9	**69.1**	67.8	**66.1**		**19.9**
H 009 X13	10	185.6	**185.7**	196.1	**193.5**	16.7	**16.9**	66.2	**66.1**	50.6	**52.8**		**19.2**
H 009 X15	60	186.4	**185.4**	194.1	**194.7**	16.2	**17.3**	66.2	**66.0**	49.8	**53.1**		**19.1**
H 009 X17	300	178.3	**178.0**	182	**186**	18.5	**16.8**	66.5	**66.2**	53.6	**64.0**		**19.3**
H 010 - 011-10	10	194.4	**192.5**	202.4	**198.1**	16.1	**16.9**	58.1	**59.1**	34.4	**35.5**		**18.7**
H 010 - 011-11	60	192.6	**191.6**	198.6	**199.4**	16.7	**16.7**	59.1	**58.2**	35.5	**34.7**		**18.7**
EAF1 RT - L19	10	160.7	**165.5**	175.1	**171.3**	21.8	**21.6**	70.8	**68.8**	66.3	**70.0**		**19.8**
EAF1 RT - L21	60	164	**163.2**	174.7	**172.5**	21.5	**21.3**	68.5	**70.6**	76.5	**69.2**		**20.3**
EAF1 RT - L23	300	162.5	**162.2**	169.3	**173.8**	22.4	**21.4**	69.5	**70.4**	65	**71.7**		**19.7**
EAF1 RT -L22	60	167.1	**161.9**	176.5	**172.8**	21.4	**21.6**	70.8	**69.5**		**72.6**		**21.1**
EAF1 RT - L24	300	162.3	**162.5**	169.9	**173.9**	21.3	**21.7**	70.4	**69.6**		**71.0**		**21.1**
H 009 X14	10	184.9	**186.1**	194.4	**193.5**	17.2	**16.9**	65.1	**63.0**		**51.2**		**21.1**
H 009 X16	60	186.4	**185.4**	193.2	**194.9**	16.6	**16.9**	61.9	**64.6**		**40.1**		**21.1**
H 009 X18	300	178.3	**177.2**	182	**185.6**	16.7	**17.4**	64.1	**63.4**		**56.5**		**21.1**
SID HT - H33-1	10	166.7	**162.9**	174.1	**169.8**	22.2	**23.3**	73.0	**73.3**		**66.9**	103.5	**104.3**
SID HT - H33-2	60	163	**162.6**	169.8	**174.1**	23.5	**22.4**	74.8	**72.9**		**66.1**	93.5	**105.1**
SID HT - H33-3	300	147.6	**138.0**	151.9	**163.1**	22.6	**23.3**	72.3	**73.7**		**66.3**	96	**105.8**
SID HT - H39-1	10	142	**144.9**	166	**161.9**	25.7	**23.4**	72.1	**73.4**		**65.9**		**104.3**
SID HT - H39-2	60	138	**142.0**	162	**165.8**	24.2	**22.3**	73.8	**73.3**		**66.2**	111	**105.1**

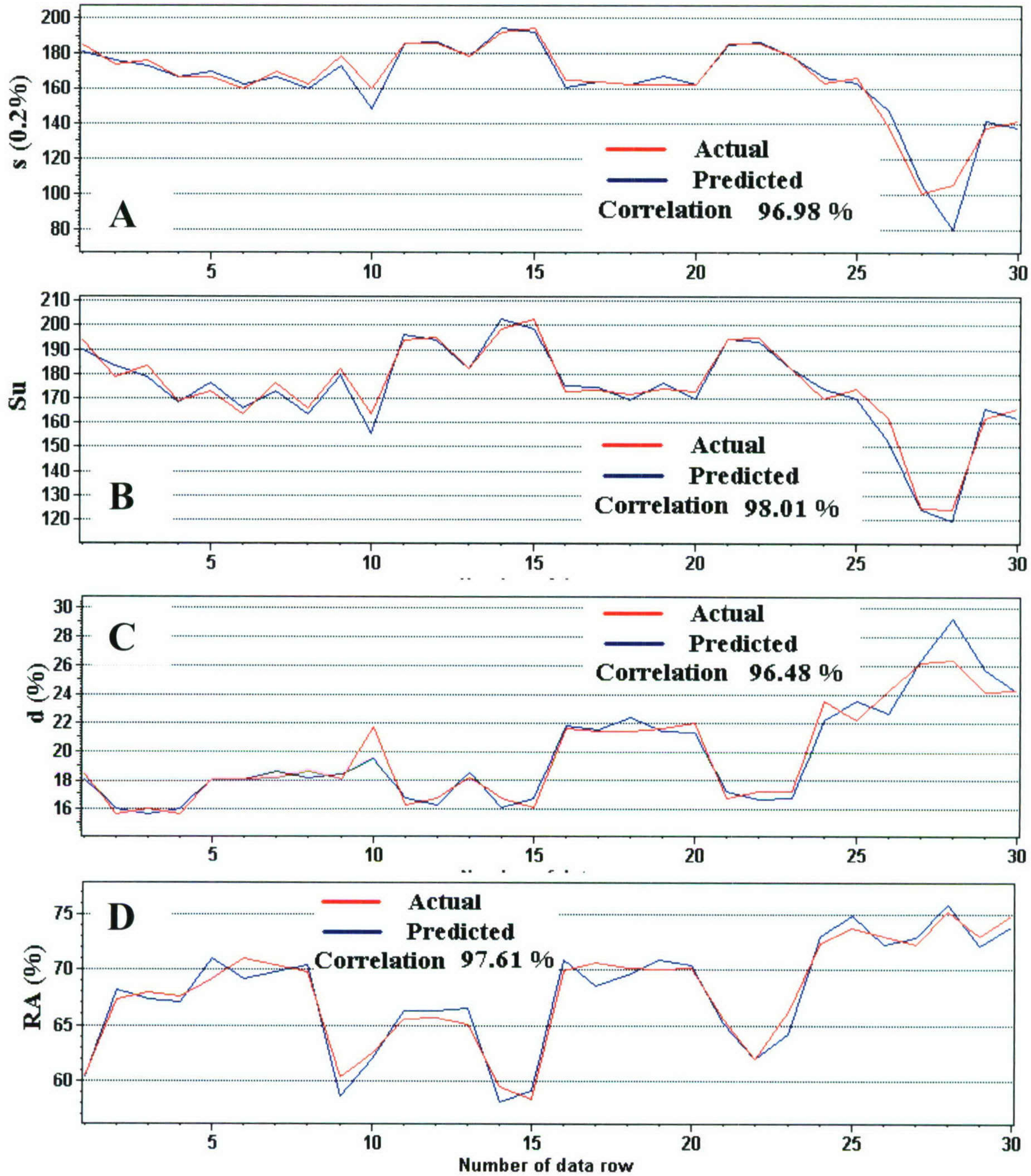


Figure 2. Correlation between the experimentally determined (A) yield strength (s (0.2%)), (B) ultimate tensile strength (Su), (C) elongation (d(%)) and (D) reduction in area of cross section (RA(%)) value versus the neural network analysis based predictions. Samples were heat treated at 1,050 °F for up to 600 minutes.

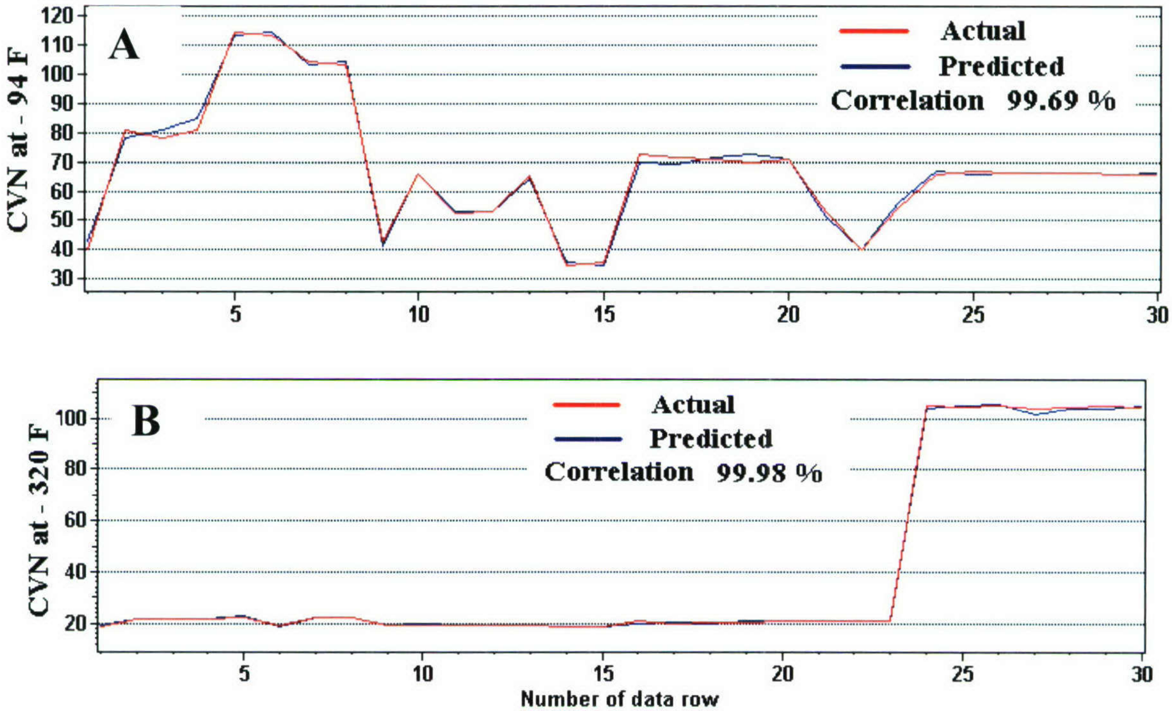


Figure 3. Correlation between the experimentally determined Charpy v-notch test (CVN) value versus the neural network analysis based predictions. CVN test temperature (A) - 94 °F and (B) – 320 °F. Samples were heat treated at 1,050 °F and for up to 600 minutes.

Once we arrived at satisfying initial predictions, we made short predictions on the mechanical properties [viz. s (0.2%), Su, d (%), RA (%) and CVN at – 94 °F and – 320 °F] by changing the heat treatment time (HTt) in the range 0 – 600 minutes. The data set was selected such that the heat treatment conditions (viz. HTT and HTt) changes for all steel samples. Therefore the final predictions provide the mechanical property values that are the average of all the different steel compositions. Figures 4 shows the typical surface plot representing the yield strength (s (0.2%)) as a function of heat treatment temperature (HTT in °F) and the heat treatment time (HTt in minutes). Figure 5 shows the dependence of yield strength (s (0.2%)) value on heat treatment time and at different heat treatment temperatures (950, 1,000, and 1,050 °F) respectively. The results suggest that the yield strength of the steel sample remains independent of heat treatment time and temperature over the range investigated here. Figure 6 shows the typical surface plot and Figure 7 shows a normal plot for the ultimate strength versus heat treatment time. Similarly Figures 8 and 9; and Figures 10 and 11 show the surface and normal plot for percent elongation (d (%)) and percent reduction in area of cross section (RA (%)) for all the steels samples heat treated up to 600 minutes at 950, 1,000, and 1,050 °F respectively. The results shown in Figures 6 – 11 suggest that, with few exceptions, the ultimate strength (Su), percent elongation (d (%)) and percent reduction in area of cross section (RA (%)) did not change with either the heat treatment temperature and/or the duration of heat treatment over 600 minutes. The scatter within the predicted values for lower heat treatment conditions is considerable. At the present time we have no possible explanation for this scatter.

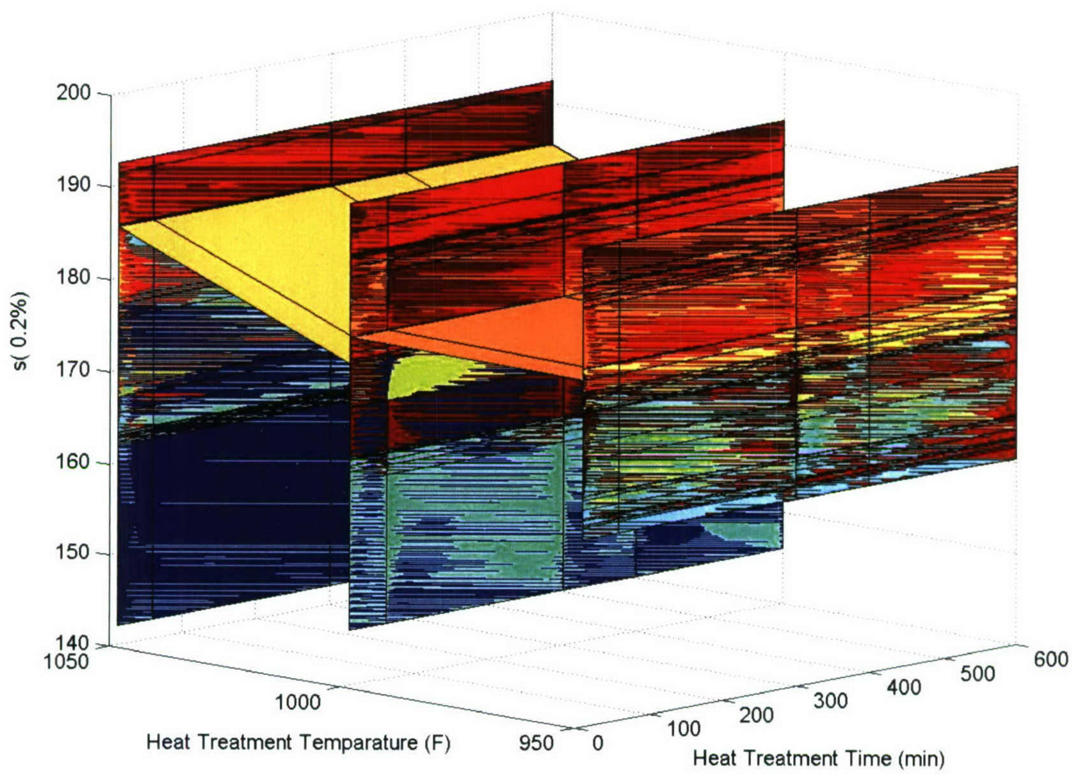


Figure 4. Typical surface map representing the yield stress (s (0.2%)) as a function of heat treatment temperature and the duration of heat treatment respectively.

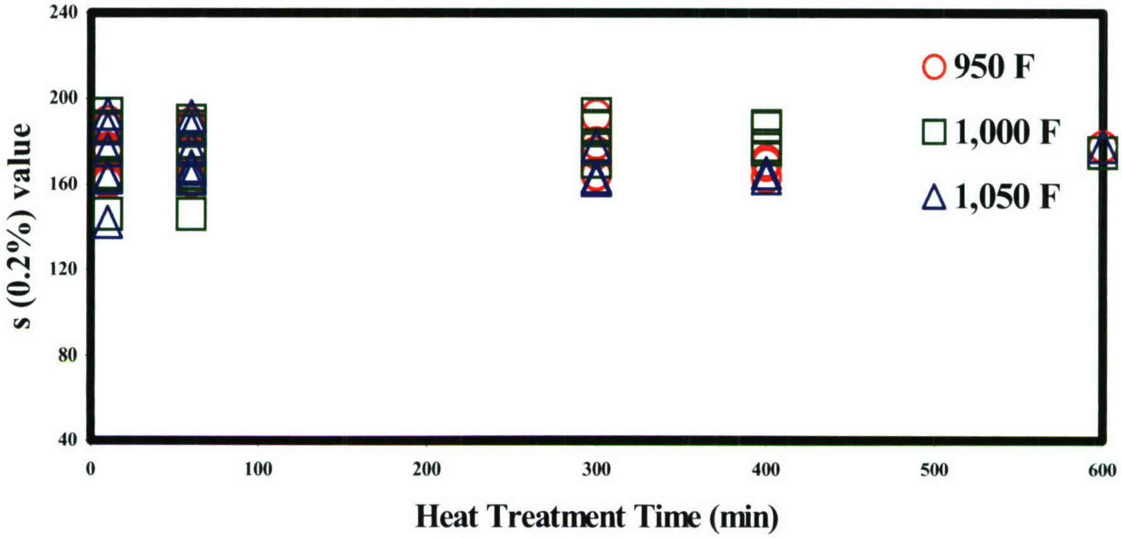


Figure 5. Predicted values of the yield stress (s (0.2%)) versus heat treatment time plot for steel samples and at different heat treatment temperatures.

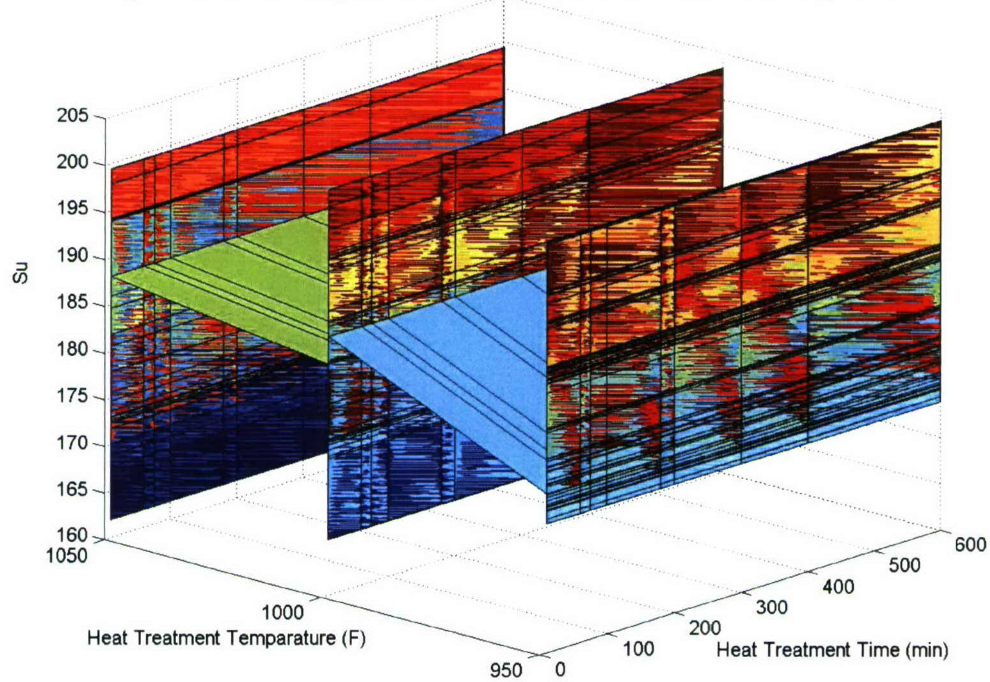


Figure 6. Typical surface map representing the ultimate tensile strength (Su) as a function of heat treatment temperature (HTT) and duration of heat treatment (HTt) respectively.

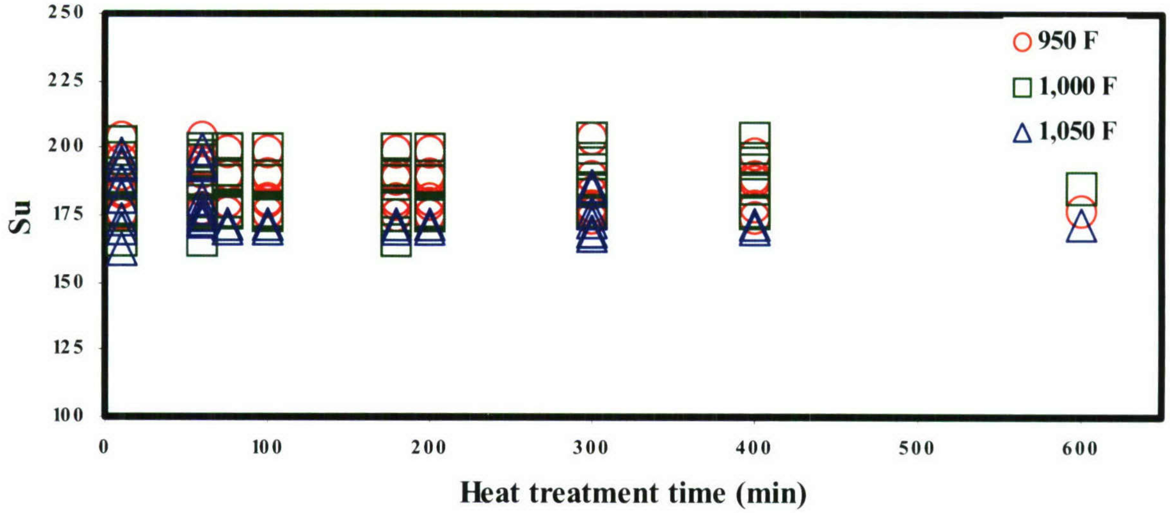


Figure 7. Predicted values of the ultimate tensile strength (Su) versus heat treatment time (HTt) plot for steel samples and at different heat treatment temperatures (HTT).

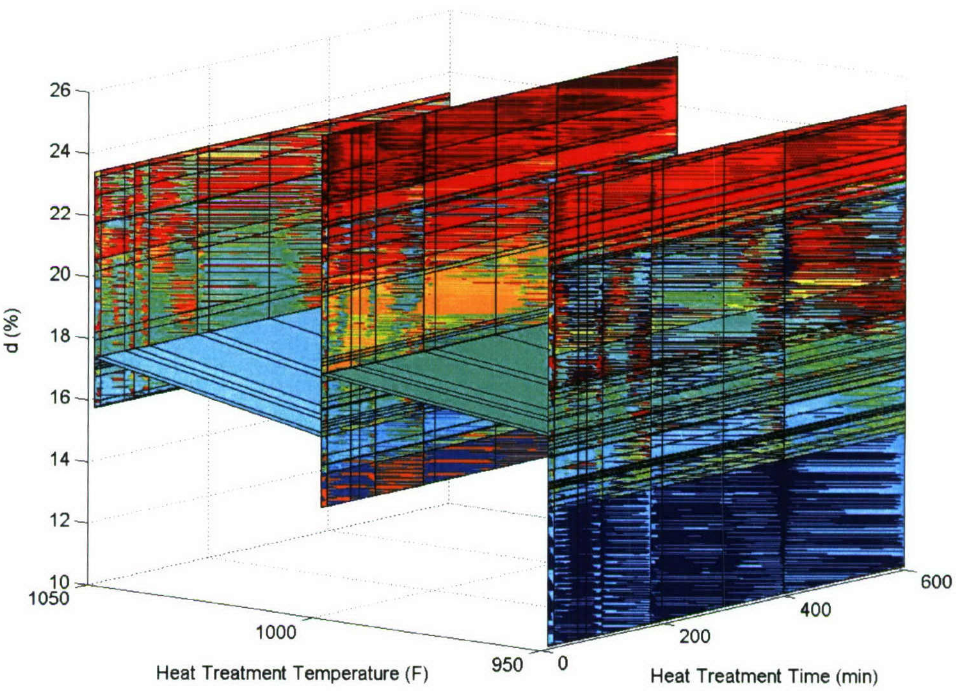


Figure 8. Typical surface map representing the elongation (d (%)) as a function of heat treatment temperature (HTT) and the duration of heat treatment (HTt) respectively.

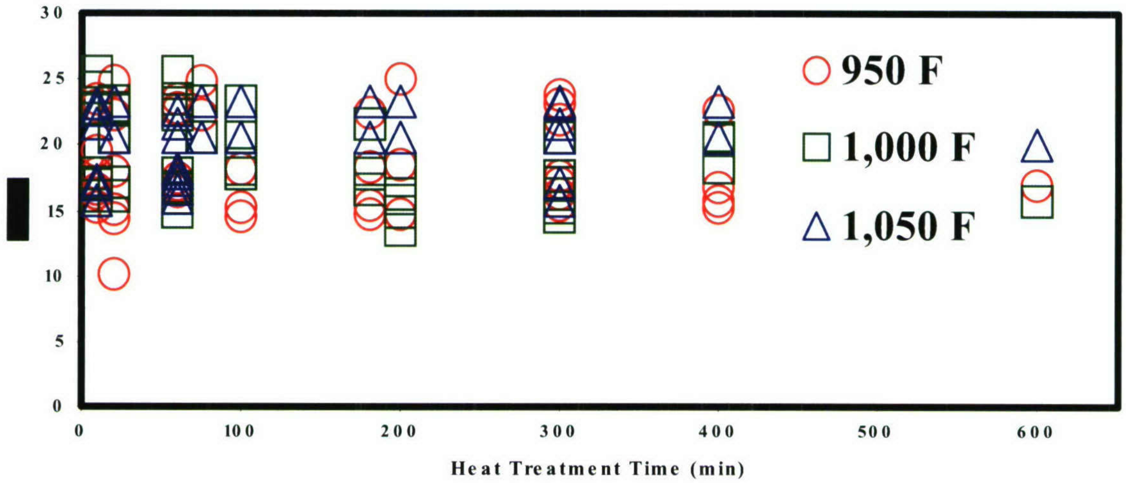


Figure 9. Predicted values of the elongation (d (%)) versus heat treatment time (HTt) plot for steel samples and at different heat treatment temperatures (HTT).

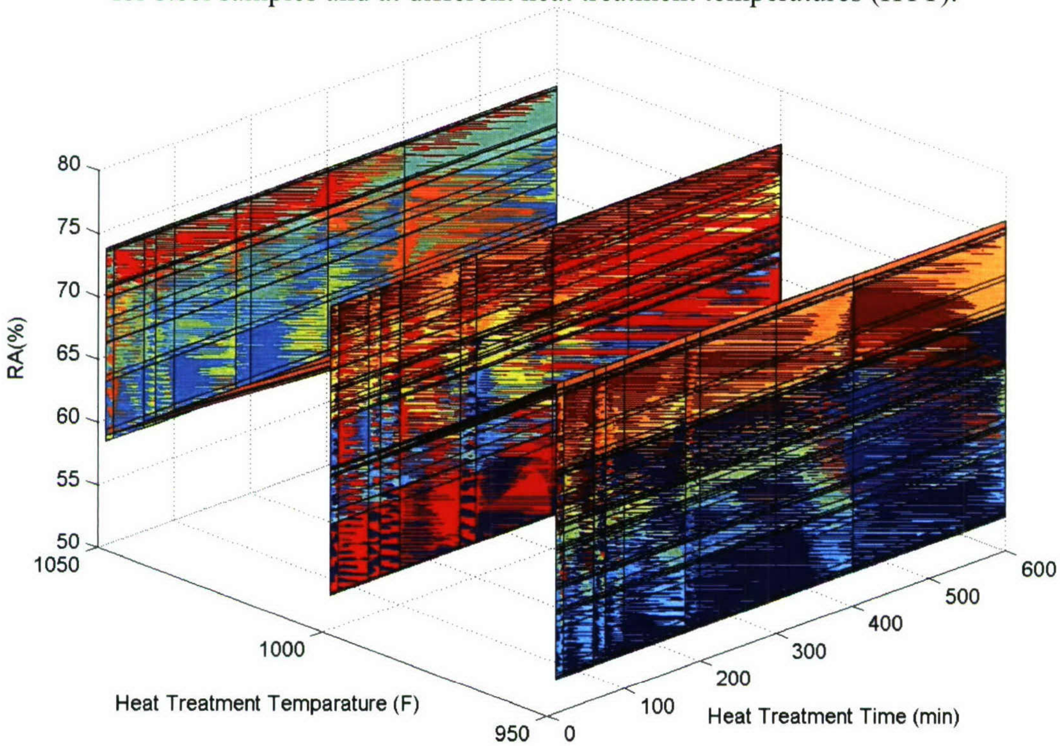


Figure 10. Typical surface map representing the reduction in area of cross section (RA(%)) as a function of heat treatment temperature (HTT) and the duration of heat treatment (HTt) respectively.

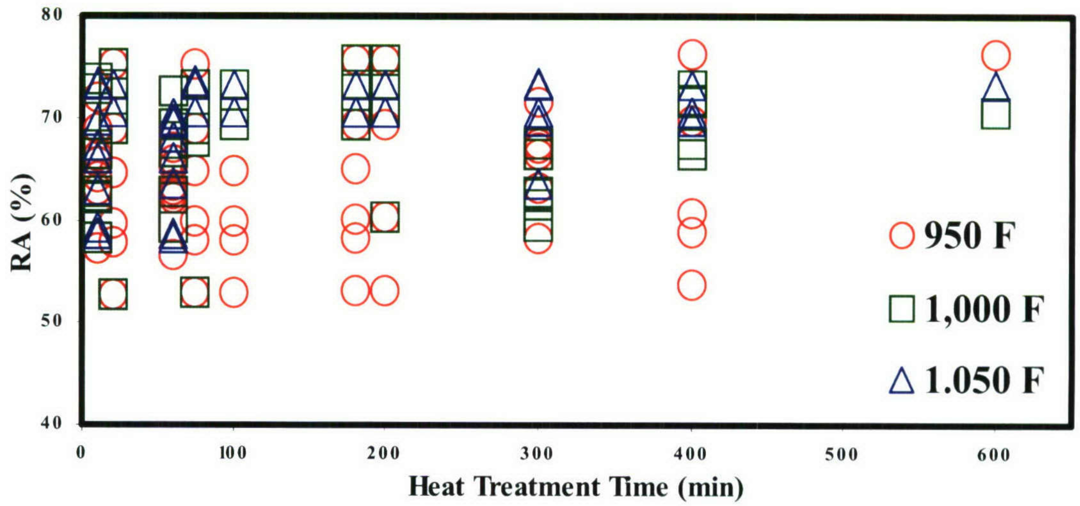


Figure 11. Predicted values of the reduction in area of cross section (RA (%)) versus heat treatment time (HTt) plot for steel samples and at different heat treatment temperatures (HTT).

In addition to the above mentioned scatter in the data, another anomaly that can be noticed in the surface plots is that the three profiles corresponding to heat treatment temperature (HTT) → 950 °F and heat treatment time (HTt) of 600 minutes, HTT → 1000 °F and HTt → 600 minutes; and HTT → 1,050 °F and HTt 600 minutes were connected. It has to be pointed out that those connecting plane features in the surface plots (Figures 4, 6, 8 and10) are not real. They are the result of computer program code only.

Once the predictions based on short duration heat treatment (HTt) conditions were completed, we retrained the network and predicted the mechanical properties [viz. s (0.2%), Su, d(%), RA (%), CVN RT, CVN (-94 °F) and CVN (-320 °F)] over long heat treatment (HTt) conditions. The neural network analysis was carried out to make predictions over 1200 minutes of heat treatment. Figures 12 - 14 show the dependence of each mechanical property value (for s (0.2%), Su, d (%) and RA (%)), on heat treatment time and at different heat treatment temperatures (950, 1,000, and 1,050 °F) respectively. The Charpy v-notch test (CVN) values (for samples heat treated at 1,050 °F) measured at – 94 °F and - 320 °F are also shown in Figure 14. The results suggest that within experimental variation the heat treatment time has no or very little effect on this mechanical property. The maximum variation of $\pm$ 10% is noticeable only during the first 120 minutes of heat treatment. It is possible that such a variation is not a true indication of the mechanical property. It only represents the scatter in the input data values. It has to be pointed out that due to lack of sufficient number of input data during this analysis, a number of data points were simply added to the input tree without considering the affect of microstructure and the phase composition of the steel samples.

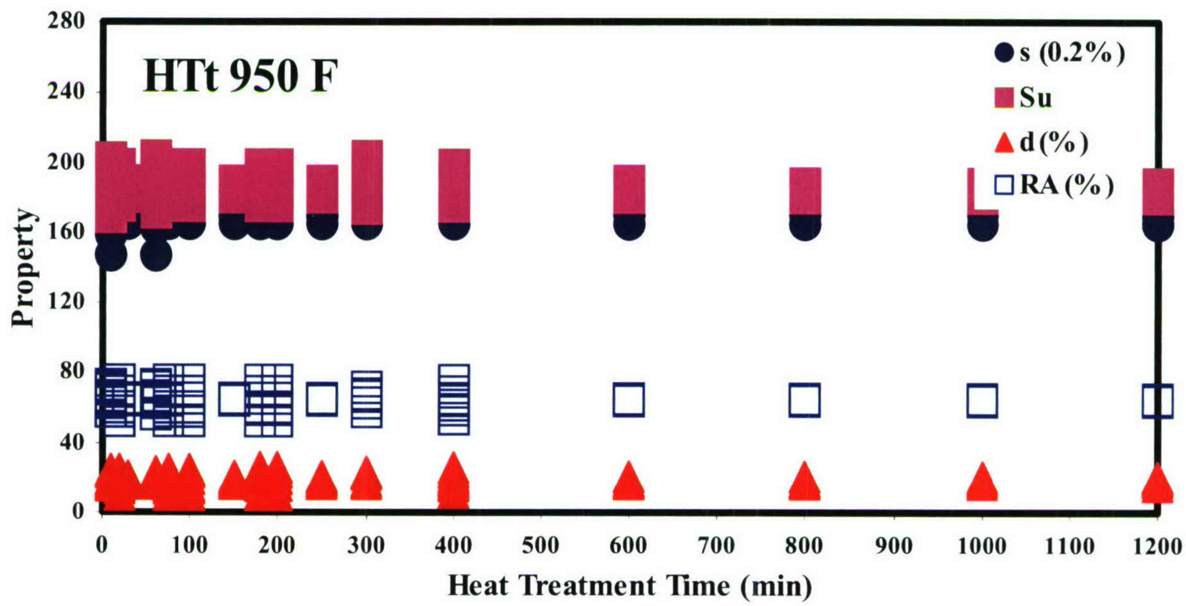


Figure 12. Predicted values of the yield stress (s (0.2%)), ultimate strength (Su), elongation (d(%)) and reduction in area of cross section (RA(%)) versus heat treatment time (HTt) plot for steel samples. The heat treatment temperature (HTT) was 950 °F.

The results shown in Figures 12 - 14 suggest that with few exceptions the mechanical property (s (0.2%), Su, d (%) and RA (%)) remains independent of the heat treatment time. Similarly, it also appears that for a given steel the heat treatment temperature (in the range 950 – 1,050 °F) has no effect on the yield strength, ultimate strength, elongation and the reduction in the area of cross section. The observed scatter in the data may be the result of many assumptions that were made for this analysis. For example, to obtain more input data points, we considered only the compositional and mechanical property data of several different steels with varying microstructural compositions. Similarly, due to lack of the input data, we repeated training with the available information and added that as a new input data. The most important factor that will impart error/scatter to the data is the elemental composition of the steel. While the steels samples with mechanical property data represent the information on steels with 10 different compositions, the network analysis averages the data and assumes an average elemental composition and predicts the mechanical property as a function of HTT and HTt.

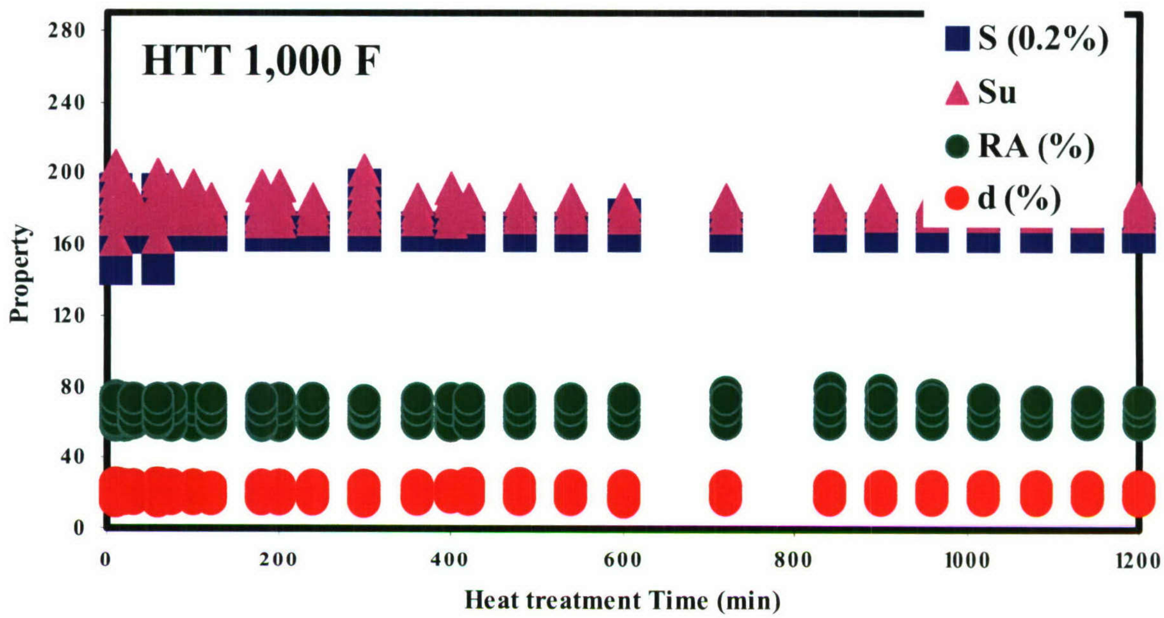


Figure 13. Predicted values of the yield stress (s (0.2%)), ultimate strength (Su), elongation (d(%)) and reduction in area of cross section (RA(%)) versus heat treatment time (HTt) plot for steel samples. The heat treatment temperatures (HTT) was 1,000 °F.

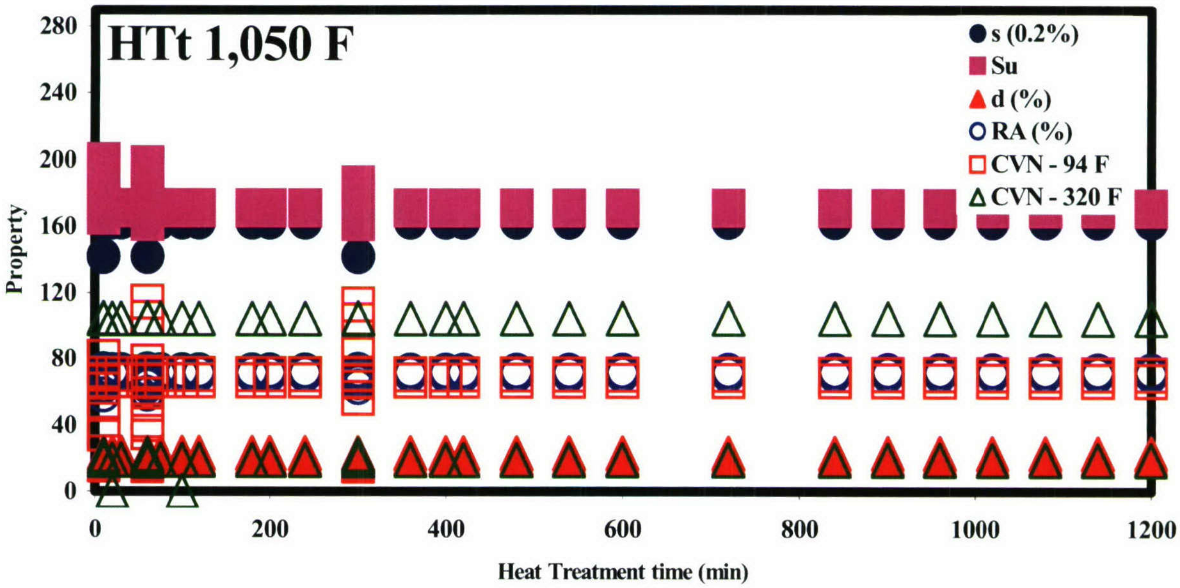


Figure 14. Predicted values of the yield stress (s (0.2%)), ultimate strength (Su), elongation (d(%)), reduction in area of cross section (RA(%)), and Chrpy v-notch test values (measured at – 94 °F and – 320 °F) versus heat treatment time (HTt) plot for steel samples. The heat treatment temperatures (HTT) was 1,050 °F.

Summary

The following conclusions can be derived from the present investigation. The neural network analysis of high carbon and high nickel steels was successfully carried out using the available data of 121 data sets obtained from 10 different steel samples. That is, the correlation between the predicted and measured results was never lower than 96%. The data sets represent several heat treatment conditions such as the heat treatment temperatures (HTT) (950, 1,000, and 1,050 °F) and the duration of heat treatment (HTt) (range 10 – 600 minutes). The results suggest that the present data, as such, is not sufficient to run a neural network analysis. However, the data is just sufficient to train the neural network using genetic mode of analysis. Once the genetic analysis based predictions were made, the predicted valued were added as additional input data so that the total number of data sets would enable a neural network mode analysis for the final predictions. The final predictions were made first over a small range of heat treatments (range 10 – 1200 minutes). The results suggest that the heat treatment has less effect on the yield strength (s(0.2%), ultimate strength (Su), elongation (d(%)) and the reduction in the area of cross section (RA(%)) than the scatter. The scatter in the data was significant only during the first 120 minutes of heat treatment where the number of data points was greatest. A possible explanation for this is that during the first 300 minutes of heat treatment, the steel samples may undergo rearrangement of their microstructure. Once the structure stabilizes, the mechanical properties remain independent of the heat treatment time. Alternatively, the scatter may be due to the fact that the steel samples have 10 different elemental compositions and different thermo-mechanical treatments (viz. hot rolling, quenching, or tempering etc.). This would also cause the steel sample phase structures to be different. Each phase structure has its own unique mechanical property value and also responds differently to a given heat treatment. Therefore the system that is being modeled may be too complex and the present network analysis approach may not be sufficient to predict the behavior.

References

1. Stergiou, C. and D. Siganos, "Artificial Neural Networks," Computer Science Dept, Imperial College London, 2000.
2. Hertz, J., A. Krogh, and R. G. Palmer, "Introduction to the Theory of Neural Networks," Pub. Addison – Wesley, 1991.

This page intentionally left blank

Distribution

DoD - CONUS	*copies*
OFFICE OF NAVAL RESEARCH ONR 332 (CHRISTODOULOU) 875 NORTH RANDOLPH ST SUITE 1425 ARLINGTON VA 22203-1995	1
COMMANDER NAVAL SEA SYSTEM COMMAND ATTN SEA 05M (KAZNOFF) 1333 ISAAC HULL AVE SE STOP 5130 WASHINGTON NAVY YARD DC 20376-5130	1
COMMANDER NAVAL SEA SYSTEMS COMMAND ATTN SEA 05M1 1333 ISAAC HULL AVE SE STOP 5132 WASHINGTON NAVY YARD DC 20376-5132	1
COMMANDER NAVAL SEA SYSTEMS COMMAND ATTN SEA 05M2 1333 ISAAC HULL AVE SE STOP 5132 WASHINGTON NAVY YARD DC 20376-5132	1
DEFENSE TECH INFORMATION CENTER 8725 JOHN J KINGMAN RD SUITE 09844 FORT BELVOIR VA 22060-6218	1

INTERNAL		*copies*
CODE 0115		1
CODE 0112		1
CODE 60		1
CODE 60	(SUDDUTH)	1
CODE 61		1
CODE 612	(RAO)	4
CODE 611		1
CODE 612		1
CODE 612	(CZYRYCA)	1
CODE 612	(FIELDER)	1
CODE 612	(GAIES)	1
CODE 612	(HAYDEN)	1
CODE 612	(MOUSSOUROS)	1
CODE 612	(PURTSCHER)	1
CODE 612	(ROE)	1
CODE 612	(STILES)	1
CODE 612	(SUTTON)	1
CODE 612	(SYLVESTER)	1
CODE 612	(WONG)	1
CODE 612	(ZHANG)	1
CODE 612	(BRANDEMARTE)	1
CODE 613		2
CODE 614		1
CODE 615		1
CODE 616		1
CODE 617		1
CODE 62		1
CODE 63		1
CODE 64		1
CODE 65		1
CODE 66		1
CODE 3442	(TIC-pdf only)	

This page intentionally left blank

NAVSEA

WARFARE CENTERS

Carderock Division